Laboratorium 2 - Wyciskanie soku

Wszystko się zaczyna i kończy na danych

In [1]:
```
from time import time
from datetime import datetime
from typing import Sequence
import IPython.display as d
import torch
import torchvision
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
import torch.utils.data as data
from torch.utils.data import Subset, ConcatDataset, DataLoader
import numpy as np
import optuna
from PIL import Image
import matplotlib.pyplot as plt


def display(*images: torch.Tensor | np.ndarray) -> None:
    if (len(images) == 0):
        return

    pil_images: list[Image.Image] | None = None
    if isinstance(images[0], torch.Tensor):
        pil_images = [transforms.ToTensor(image.to(torch.uint8)) for imag
    else:
        print(images[0])
        pil_images = [
            Image.fromarray(image.astype(np.uint8)) for image in images
        ]

    d.display(*pil_images)


def display_dataset_image(image: torch.Tensor, image_class: str) -> None:
    # Transpose image from (C, H, W) to (H, W, C).
    image = image.permute(1, 2, 0)

    plt.imshow(image)
    plt.axis("off")
    plt.title(image_class.capitalize())
    plt.show()
```

```
/Users/szary/.local/share/virtualenvs/lab2-image-classification-z_Vd5T3Q/l
ib/python3.12/site-packages/tqdm/auto.py:21: TqdmWarning: IProgress not fo
und. Please update jupyter and ipywidgets. See https://ipywidgets.readthed
ocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

In [2]:
```
batch_size = 64
worker_count = 4
```

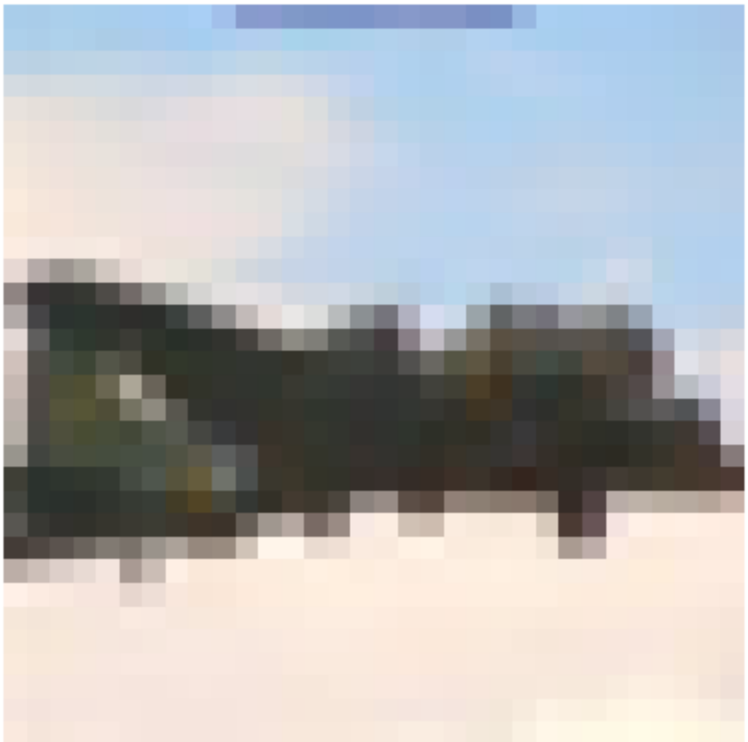
```python
transform = transforms.Compose([
    transforms.ToTensor(),
])

trainset, valset = data.random_split(
    torchvision.datasets.CIFAR10(
        root="./data", train=True, download=True, transform=transform
    ),
    lengths=(.9, .1),
    generator=torch.Generator().manual_seed(2137)
)
trainloader = DataLoader(
    trainset, batch_size=batch_size, shuffle=True, num_workers=worker_cou
)
valloader = DataLoader(
    valset, batch_size=batch_size, shuffle=False, num_workers=worker_coun
)

testset = torchvision.datasets.CIFAR10(
    root="./data", train=False, download=True, transform=transform
)
testloader = DataLoader(
    testset, batch_size=batch_size, shuffle=False, num_workers=worker_cou
)

classes = ("plane", "car", "bird", "cat",
           "deer", "dog", "frog", "horse", "ship", "truck")
```

```
Files already downloaded and verified
Files already downloaded and verified
```

In [3]:

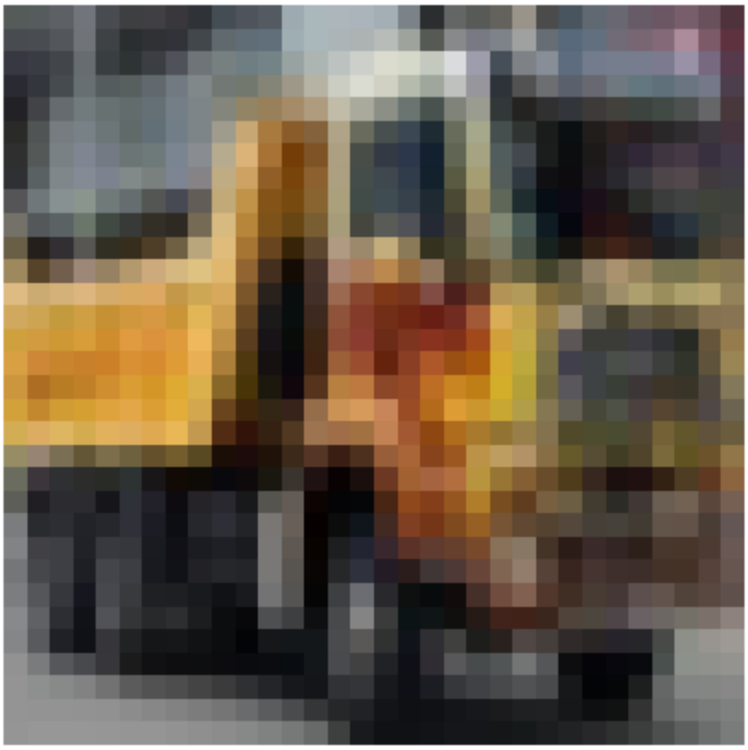
```python
for image, class_index in ConcatDataset([
    Subset(trainset, torch.arange(21, 23)),
    Subset(valset, torch.arange(37, 39)),
    Subset(testset, torch.arange(42, 44)),
]):
    display_dataset_image(image, classes[class_index])
```

Plane



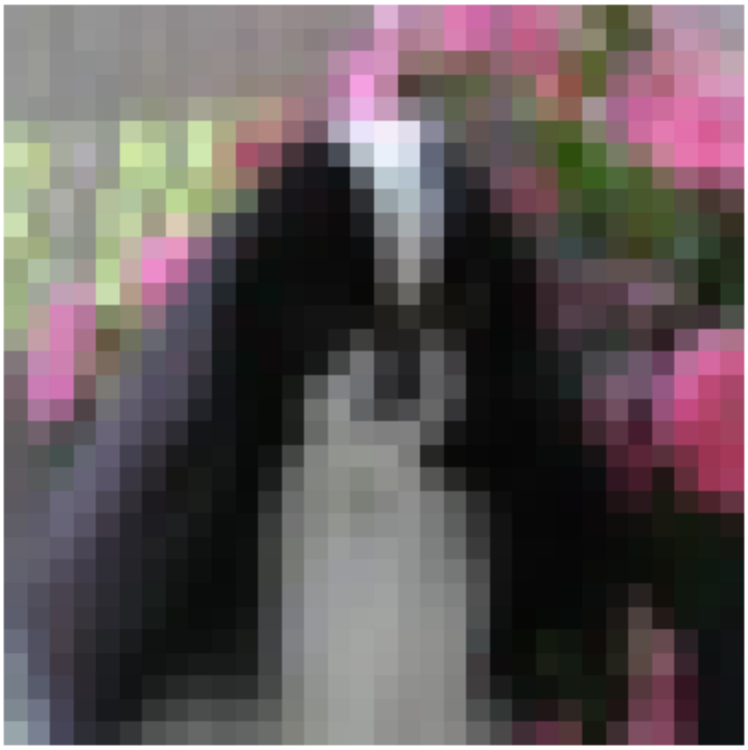
Plane

Truck

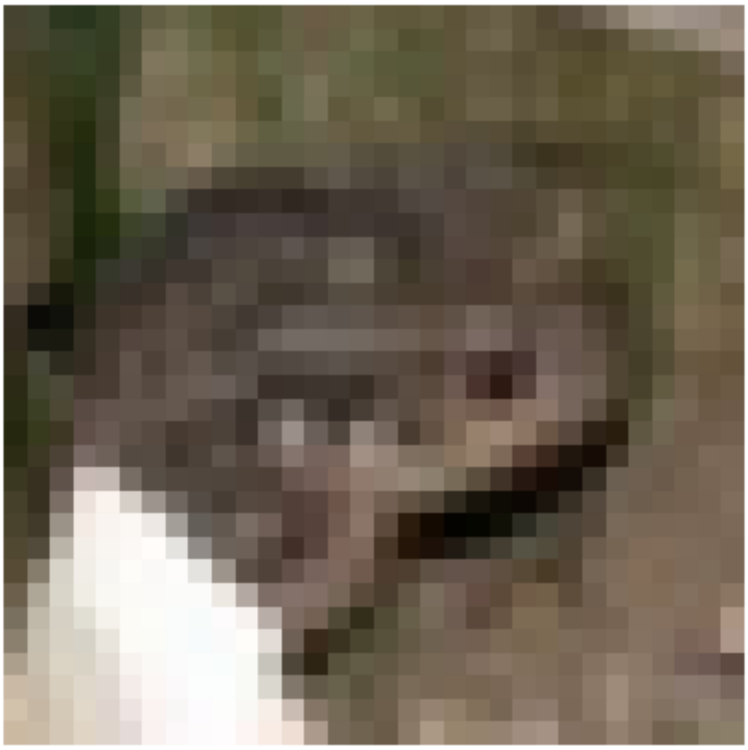


Bird

Dog



Frog



Projektujemy architekturę sieci neuronowej

Bazową strukturę postanowiłem wzbogacić o przejścia rezydualne. Każda warstwa konwolucyjna to w zasadzie cztery powielone warstwy, które posiadają dwa przejścia. Poniżej zamieszczam implementację mojej architektury w PyTorch.

In [4]:
```
class ResidualBlock(nn.Module):
    def __init__(
```

```
        self,
        subblock_index: int,
        in_channels: int,
        out_channels: int,
        kernel_size=3
    ):
        super().__init__()

        self.relu = nn.ReLU(inplace=True)

        self.projection: nn.Module | None = None
        if in_channels != out_channels:
            self.projection = nn.Sequential(
                nn.Conv2d(in_channels, out_channels, kernel_size=kernel_s
                nn.BatchNorm2d(out_channels)
            )

        self.layer1 = nn.Sequential(
            nn.Conv2d(
                in_channels,
                out_channels,
                kernel_size=kernel_size,
                padding=0 if subblock_index == 0 else kernel_size // 2,
                bias=False
            ),
            nn.BatchNorm2d(out_channels)
        )
        self.layer2 = nn.Sequential(
            nn.Conv2d(
                out_channels,
                out_channels,
                kernel_size=kernel_size,
                padding=kernel_size // 2,
                bias=False
            ),
            nn.BatchNorm2d(out_channels)
        )

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        residual = x if self.projection is None else self.projection(x)

        out = self.layer1(x)
        out = self.relu(out)

        out = self.layer2(out)
        out += residual
        out = self.relu(out)

        return out


class ForceNet(nn.Module):
    def __init__(self, layers: Sequence[int], class_count=1_000):
        super().__init__()

        self.in_channels = 3

        # ResNet layers.
        self.layer1 = self.__make_layer(6, layers[0])
        self.layer2 = self.__make_layer(16, layers[1])
```

```python
        self.final_layer = nn.Sequential(
            nn.Flatten(),
            nn.Linear(in_features=400, out_features=120),
            nn.ReLU(inplace=True),
            nn.Linear(in_features=120, out_features=84),
            nn.ReLU(inplace=True),
            nn.Linear(in_features=84, out_features=class_count),
        )

    def __make_layer(
        self,
        out_channels: int,
        block_count: int,
    ) -> nn.Sequential:
        blocks: list[nn.Module] = [
            ResidualBlock(
                subblock_index=0,
                in_channels=self.in_channels,
                out_channels=out_channels,
                kernel_size=5
            )
        ]
        self.in_channels = out_channels
        for i in range(1, block_count):
            blocks.append(ResidualBlock(
                subblock_index=i,
                in_channels=self.in_channels,
                out_channels=out_channels,
                kernel_size=5
            ))

        return nn.Sequential(*blocks, nn.AvgPool2d(kernel_size=2, stride=

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        x = self.layer1(x)
        x = self.layer2(x)
        x = self.final_layer(x)

        return x


model = ForceNet(layers=(2, 2), class_count=len(classes))
```

In [5]:

```python
print(model)

print()

count: int = 0
for name, param in model.named_parameters():
    count += 1
    print(name)
print(f"Total: {count}.")
```

```
ForceNet(
  (layer1): Sequential(
    (0): ResidualBlock(
      (relu): ReLU(inplace=True)
      (projection): Sequential(
        (0): Conv2d(3, 6, kernel_size=(5, 5), stride=(1, 1))
        (1): BatchNorm2d(6, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_stats=True)
      )
      (layer1): Sequential(
        (0): Conv2d(3, 6, kernel_size=(5, 5), stride=(1, 1), bias=False)
        (1): BatchNorm2d(6, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_stats=True)
      )
      (layer2): Sequential(
        (0): Conv2d(6, 6, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2), bias=False)
        (1): BatchNorm2d(6, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_stats=True)
      )
    )
    (1): ResidualBlock(
      (relu): ReLU(inplace=True)
      (layer1): Sequential(
        (0): Conv2d(6, 6, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2), bias=False)
        (1): BatchNorm2d(6, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_stats=True)
      )
      (layer2): Sequential(
        (0): Conv2d(6, 6, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2), bias=False)
        (1): BatchNorm2d(6, eps=1e-05, momentum=0.1, affine=True, track_ru
nning_stats=True)
      )
    )
    (2): AvgPool2d(kernel_size=2, stride=2, padding=0)
  )
  (layer2): Sequential(
    (0): ResidualBlock(
      (relu): ReLU(inplace=True)
      (projection): Sequential(
        (0): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
        (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
      )
      (layer1): Sequential(
        (0): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1), bias=False)
        (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
      )
      (layer2): Sequential(
        (0): Conv2d(16, 16, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2), bias=False)
        (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
      )
    )
    (1): ResidualBlock(
      (relu): ReLU(inplace=True)
```

```
      (layer1): Sequential(
        (0): Conv2d(16, 16, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2), bias=False)
        (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
      )
      (layer2): Sequential(
        (0): Conv2d(16, 16, kernel_size=(5, 5), stride=(1, 1), padding=(2,
2), bias=False)
        (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_r
unning_stats=True)
      )
    )
    (2): AvgPool2d(kernel_size=2, stride=2, padding=0)
  )
  (final_layer): Sequential(
    (0): Flatten(start_dim=1, end_dim=-1)
    (1): Linear(in_features=400, out_features=120, bias=True)
    (2): ReLU(inplace=True)
    (3): Linear(in_features=120, out_features=84, bias=True)
    (4): ReLU(inplace=True)
    (5): Linear(in_features=84, out_features=10, bias=True)
  )
)

layer1.0.projection.0.weight
layer1.0.projection.0.bias
layer1.0.projection.1.weight
layer1.0.projection.1.bias
layer1.0.layer1.0.weight
layer1.0.layer1.1.weight
layer1.0.layer1.1.bias
layer1.0.layer2.0.weight
layer1.0.layer2.1.weight
layer1.0.layer2.1.bias
layer1.1.layer1.0.weight
layer1.1.layer1.1.weight
layer1.1.layer1.1.bias
layer1.1.layer2.0.weight
layer1.1.layer2.1.weight
layer1.1.layer2.1.bias
layer2.0.projection.0.weight
layer2.0.projection.0.bias
layer2.0.projection.1.weight
layer2.0.projection.1.bias
layer2.0.layer1.0.weight
layer2.0.layer1.1.weight
layer2.0.layer1.1.bias
layer2.0.layer2.0.weight
layer2.0.layer2.1.weight
layer2.0.layer2.1.bias
layer2.1.layer1.0.weight
layer2.1.layer1.1.weight
layer2.1.layer1.1.bias
layer2.1.layer2.0.weight
layer2.1.layer2.1.weight
layer2.1.layer2.1.bias
final_layer.1.weight
final_layer.1.bias
final_layer.3.weight
```

```
final_layer.3.bias
final_layer.5.weight
final_layer.5.bias
Total: 38.
```

W PyTorchu nie potrzeba inicjalizować wag sieci neuronowej. PyTorch automatycznie i niejawnie korzysta z inicjalizacji dystrybucji Kaiminga He dla warstw konwolucyjnych i liniowych. Można także manualnie zainicjalizować warstwy za pomocą modułu `torch.nn.init`.

Zapętlamy się w treningu

Do treningu, walidacji wykorzystałem funkcję kosztu Categorical Cross-Entropy Loss i optymalizatora Adam.

In [6]:
```python
# Create the ForceNet (LeNet-5 and ResNet combination).
model = ForceNet(layers=(2, 2), class_count=len(classes))

# Move model to GPU if available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = model.to(device)

# Define the loss function and optimizer.
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=.001)
```

In [7]:
```python
def train_and_validate(
    model: nn.Module,
    trainloader: DataLoader,
    valloader: DataLoader,
    criterion: nn.Module,
    optimizer: optim.Optimizer,
    device: torch.device | None = None,
    epoch_count: int = 10
) -> None:
    def log(epoch: int, message: str) -> None:
        pretty_date: str = datetime.now().strftime("%Y-%m-%d %H:%M:%S")
        print(f"{pretty_date} - Epoch [{epoch + 1}/{epoch_count}] - {mess

    if device is None:
        device = torch.device("cuda" if torch.cuda.is_available() else "c

    log_interval: float = 10.  # In seconds.

    for epoch in range(epoch_count):
        log(epoch, "Starting training.")

        cumulative_train_loss: float = 0.
        model.train()
        base_time: float = time()
        for inputs, labels in trainloader:
            inputs, labels = inputs.to(device), labels.to(device)

            current_time: float = time()
            if current_time - base_time >= log_interval:
                base_time = current_time
```

```python
                average_train_loss: float \
                    = cumulative_train_loss / len(trainloader)
                log(epoch, f"Train Loss: {average_train_loss:.4f}.")

            optimizer.zero_grad()

            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            cumulative_train_loss += loss.item()

        log(epoch, "Training finished.")

        average_train_loss: float = cumulative_train_loss / len(trainload

        log(epoch, "Starting validation.")

        cumulative_val_loss: float = 0.
        correct: int = 0
        total: int = 0
        model.eval()
        base_time = time()
        with torch.no_grad():
            for inputs, labels in valloader:
                inputs, labels = inputs.to(device), labels.to(device)

                current_time: float = time()
                if current_time - base_time >= log_interval:
                    base_time = current_time
                    average_val_loss: float \
                        = cumulative_val_loss / len(valloader)
                    log(epoch, f"Validation Loss: {average_val_loss:.4f}.

                outputs = model(inputs)
                loss = criterion(outputs, labels)
                cumulative_val_loss += loss.item()
                _, predicted = torch.max(outputs.data, dim=1)

                total += labels.size(dim=0)
                correct += (predicted == labels).sum().item()

        average_val_loss = cumulative_val_loss / len(valloader)
        val_accuracy = correct / total

        log(epoch, "Validation finished.")

        log(
            epoch,
            f"Train Loss: {average_train_loss:.4f}, "
                f"Validation Loss: {average_val_loss:.4f}, "
                f"Validation Accuracy: {val_accuracy:.2%}."
        )
```

In [8]:

```python
def test(
    model: nn.Module,
    testloader: DataLoader,
    criterion: nn.Module,
    device: torch.device | None = None,
```

```python
) -> float:
    model.eval()
    cumulative_loss: float = 0.
    correct: int = 0
    total: int = 0

    with torch.no_grad():
        for inputs, labels in testloader:
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = model(inputs)
            loss = criterion(outputs, labels)
            cumulative_loss += loss.item()
            _, predicted = torch.max(outputs.data, dim=1)

            total += labels.size(dim=0)
            correct += (predicted == labels).sum().item()

    test_accuracy = correct / total

    print(
        f"Test Loss: {cumulative_loss / len(testloader):.4f} "
        f"Test Accuracy: {test_accuracy:.2%}."
    )

    return test_accuracy
```

Uzyskane wyniki

Trening

```
plain
2024-11-02 22:19:57 - Epoch [1/10] - Train Loss: 0.0475.
2024-11-02 22:20:07 - Epoch [1/10] - Train Loss: 0.2511.
2024-11-02 22:20:17 - Epoch [1/10] - Train Loss: 0.4468.
2024-11-02 22:20:27 - Epoch [1/10] - Train Loss: 0.6606.
2024-11-02 22:20:37 - Epoch [1/10] - Train Loss: 0.8707.
2024-11-02 22:20:47 - Epoch [1/10] - Train Loss: 1.0746.
2024-11-02 22:20:57 - Epoch [1/10] - Train Loss: 1.2473.
2024-11-02 22:21:07 - Epoch [1/10] - Train Loss: 1.4131.
2024-11-02 22:21:30 - Epoch [1/10] - Training finished.
2024-11-02 22:21:30 - Epoch [1/10] - Starting validation.
2024-11-02 22:21:59 - Epoch [1/10] - Validation finished.
2024-11-02 22:21:59 - Epoch [1/10] - Train Loss: 1.4604,
Validation Loss: 1.2996, Validation Accuracy: 52.60%.
2024-11-02 22:21:59 - Epoch [2/10] - Starting training.
2024-11-02 22:22:09 - Epoch [2/10] - Train Loss: 0.0429.
2024-11-02 22:22:19 - Epoch [2/10] - Train Loss: 0.2066.
2024-11-02 22:22:29 - Epoch [2/10] - Train Loss: 0.3646.
2024-11-02 22:22:39 - Epoch [2/10] - Train Loss: 0.5179.
2024-11-02 22:22:49 - Epoch [2/10] - Train Loss: 0.6716.
2024-11-02 22:22:59 - Epoch [2/10] - Train Loss: 0.8267.
2024-11-02 22:23:09 - Epoch [2/10] - Train Loss: 0.9651.
2024-11-02 22:23:19 - Epoch [2/10] - Train Loss: 1.1115.
2024-11-02 22:23:41 - Epoch [2/10] - Training finished.
2024-11-02 22:23:41 - Epoch [2/10] - Starting validation.
2024-11-02 22:24:10 - Epoch [2/10] - Validation finished.
```

```
2024-11-02 22:24:10 - Epoch [2/10] - Train Loss: 1.1313,
Validation Loss: 1.0968, Validation Accuracy: 60.76%.
2024-11-02 22:24:10 - Epoch [3/10] - Starting training.
2024-11-02 22:24:20 - Epoch [3/10] - Train Loss: 0.0380.
2024-11-02 22:24:30 - Epoch [3/10] - Train Loss: 0.1781.
2024-11-02 22:24:40 - Epoch [3/10] - Train Loss: 0.3139.
2024-11-02 22:24:50 - Epoch [3/10] - Train Loss: 0.4454.
2024-11-02 22:25:00 - Epoch [3/10] - Train Loss: 0.5732.
2024-11-02 22:25:10 - Epoch [3/10] - Train Loss: 0.7009.
2024-11-02 22:25:20 - Epoch [3/10] - Train Loss: 0.8297.
2024-11-02 22:25:30 - Epoch [3/10] - Train Loss: 0.9539.
2024-11-02 22:25:53 - Epoch [3/10] - Training finished.
2024-11-02 22:25:53 - Epoch [3/10] - Starting validation.
2024-11-02 22:26:22 - Epoch [3/10] - Validation finished.
2024-11-02 22:26:22 - Epoch [3/10] - Train Loss: 0.9889,
Validation Loss: 1.0985, Validation Accuracy: 61.12%.
2024-11-02 22:26:22 - Epoch [4/10] - Starting training.
2024-11-02 22:26:32 - Epoch [4/10] - Train Loss: 0.0278.
2024-11-02 22:26:42 - Epoch [4/10] - Train Loss: 0.1526.
2024-11-02 22:26:52 - Epoch [4/10] - Train Loss: 0.2747.
2024-11-02 22:27:02 - Epoch [4/10] - Train Loss: 0.4002.
2024-11-02 22:27:12 - Epoch [4/10] - Train Loss: 0.5184.
2024-11-02 22:27:22 - Epoch [4/10] - Train Loss: 0.6340.
2024-11-02 22:27:32 - Epoch [4/10] - Train Loss: 0.7528.
2024-11-02 22:27:42 - Epoch [4/10] - Train Loss: 0.8732.
2024-11-02 22:28:04 - Epoch [4/10] - Training finished.
2024-11-02 22:28:04 - Epoch [4/10] - Starting validation.
2024-11-02 22:28:33 - Epoch [4/10] - Validation finished.
2024-11-02 22:28:33 - Epoch [4/10] - Train Loss: 0.9053,
Validation Loss: 1.2109, Validation Accuracy: 58.90%.
2024-11-02 22:28:33 - Epoch [5/10] - Starting training.
2024-11-02 22:28:43 - Epoch [5/10] - Train Loss: 0.0301.
2024-11-02 22:28:53 - Epoch [5/10] - Train Loss: 0.1437.
2024-11-02 22:29:04 - Epoch [5/10] - Train Loss: 0.2587.
2024-11-02 22:29:14 - Epoch [5/10] - Train Loss: 0.3710.
2024-11-02 22:29:24 - Epoch [5/10] - Train Loss: 0.4794.
2024-11-02 22:29:34 - Epoch [5/10] - Train Loss: 0.5966.
2024-11-02 22:29:44 - Epoch [5/10] - Train Loss: 0.7100.
2024-11-02 22:29:54 - Epoch [5/10] - Train Loss: 0.8200.
2024-11-02 22:30:16 - Epoch [5/10] - Training finished.
2024-11-02 22:30:16 - Epoch [5/10] - Starting validation.
2024-11-02 22:30:45 - Epoch [5/10] - Validation finished.
2024-11-02 22:30:45 - Epoch [5/10] - Train Loss: 0.8381,
Validation Loss: 0.9251, Validation Accuracy: 67.14%.
2024-11-02 22:30:45 - Epoch [6/10] - Starting training.
2024-11-02 22:30:55 - Epoch [6/10] - Train Loss: 0.0233.
2024-11-02 22:31:05 - Epoch [6/10] - Train Loss: 0.1218.
2024-11-02 22:31:15 - Epoch [6/10] - Train Loss: 0.2169.
2024-11-02 22:31:25 - Epoch [6/10] - Train Loss: 0.3146.
2024-11-02 22:31:35 - Epoch [6/10] - Train Loss: 0.4085.
2024-11-02 22:31:45 - Epoch [6/10] - Train Loss: 0.5135.
2024-11-02 22:31:55 - Epoch [6/10] - Train Loss: 0.6133.
2024-11-02 22:32:05 - Epoch [6/10] - Train Loss: 0.7102.
2024-11-02 22:32:33 - Epoch [6/10] - Training finished.
2024-11-02 22:32:33 - Epoch [6/10] - Starting validation.
2024-11-02 22:33:03 - Epoch [6/10] - Validation finished.
```

```
2024-11-02 22:33:03 - Epoch [6/10] - Train Loss: 0.7880,
Validation Loss: 0.9210, Validation Accuracy: 68.24%.
2024-11-02 22:33:03 - Epoch [7/10] - Starting training.
2024-11-02 22:33:13 - Epoch [7/10] - Train Loss: 0.0192.
2024-11-02 22:33:23 - Epoch [7/10] - Train Loss: 0.1122.
2024-11-02 22:33:33 - Epoch [7/10] - Train Loss: 0.2062.
2024-11-02 22:33:43 - Epoch [7/10] - Train Loss: 0.2968.
2024-11-02 22:33:53 - Epoch [7/10] - Train Loss: 0.3912.
2024-11-02 22:34:03 - Epoch [7/10] - Train Loss: 0.4866.
2024-11-02 22:34:13 - Epoch [7/10] - Train Loss: 0.5816.
2024-11-02 22:34:23 - Epoch [7/10] - Train Loss: 0.6763.
2024-11-02 22:34:49 - Epoch [7/10] - Training finished.
2024-11-02 22:34:49 - Epoch [7/10] - Starting validation.
2024-11-02 22:35:19 - Epoch [7/10] - Validation finished.
2024-11-02 22:35:19 - Epoch [7/10] - Train Loss: 0.7368,
Validation Loss: 0.9525, Validation Accuracy: 67.60%.
2024-11-02 22:35:19 - Epoch [8/10] - Starting training.
2024-11-02 22:35:29 - Epoch [8/10] - Train Loss: 0.0217.
2024-11-02 22:35:39 - Epoch [8/10] - Train Loss: 0.1039.
2024-11-02 22:35:49 - Epoch [8/10] - Train Loss: 0.1946.
2024-11-02 22:35:59 - Epoch [8/10] - Train Loss: 0.2828.
2024-11-02 22:36:09 - Epoch [8/10] - Train Loss: 0.3619.
2024-11-02 22:36:19 - Epoch [8/10] - Train Loss: 0.4382.
2024-11-02 22:36:29 - Epoch [8/10] - Train Loss: 0.5315.
2024-11-02 22:36:39 - Epoch [8/10] - Train Loss: 0.6176.
2024-11-02 22:37:08 - Epoch [8/10] - Training finished.
2024-11-02 22:37:08 - Epoch [8/10] - Starting validation.
2024-11-02 22:37:38 - Epoch [8/10] - Validation finished.
2024-11-02 22:37:38 - Epoch [8/10] - Train Loss: 0.6961,
Validation Loss: 0.8447, Validation Accuracy: 70.76%.
2024-11-02 22:37:38 - Epoch [9/10] - Starting training.
2024-11-02 22:37:48 - Epoch [9/10] - Train Loss: 0.0207.
2024-11-02 22:37:58 - Epoch [9/10] - Train Loss: 0.1046.
2024-11-02 22:38:08 - Epoch [9/10] - Train Loss: 0.1909.
2024-11-02 22:38:18 - Epoch [9/10] - Train Loss: 0.2736.
2024-11-02 22:38:28 - Epoch [9/10] - Train Loss: 0.3579.
2024-11-02 22:38:38 - Epoch [9/10] - Train Loss: 0.4395.
2024-11-02 22:38:48 - Epoch [9/10] - Train Loss: 0.5236.
2024-11-02 22:38:58 - Epoch [9/10] - Train Loss: 0.6089.
2024-11-02 22:39:24 - Epoch [9/10] - Training finished.
2024-11-02 22:39:24 - Epoch [9/10] - Starting validation.
2024-11-02 22:39:53 - Epoch [9/10] - Validation finished.
2024-11-02 22:39:53 - Epoch [9/10] - Train Loss: 0.6571,
Validation Loss: 0.8988, Validation Accuracy: 68.94%.
2024-11-02 22:39:53 - Epoch [10/10] - Starting training.
2024-11-02 22:40:03 - Epoch [10/10] - Train Loss: 0.0165.
2024-11-02 22:40:13 - Epoch [10/10] - Train Loss: 0.0907.
2024-11-02 22:40:23 - Epoch [10/10] - Train Loss: 0.1668.
2024-11-02 22:40:33 - Epoch [10/10] - Train Loss: 0.2410.
2024-11-02 22:40:44 - Epoch [10/10] - Train Loss: 0.3212.
2024-11-02 22:40:54 - Epoch [10/10] - Train Loss: 0.4014.
2024-11-02 22:41:04 - Epoch [10/10] - Train Loss: 0.4791.
2024-11-02 22:41:14 - Epoch [10/10] - Train Loss: 0.5594.
2024-11-02 22:41:41 - Epoch [10/10] - Training finished.
2024-11-02 22:41:41 - Epoch [10/10] - Starting validation.
2024-11-02 22:42:11 - Epoch [10/10] - Validation finished.
```

```
2024-11-02 22:42:11 - Epoch [10/10] - Train Loss: 0.6226,
Validation Loss: 0.8379, Validation Accuracy: 71.74%.
```

Sprawdzenie poprawności

Koszt wyniósł 0.8413, a dokładność 71.79%.

Hiperparametryzujemy sieć i jej trening

Do poszukiwania jak najlepszych hiperparametrów wybrałem framework Optuna. Przeszukiwanie przestrzeni działa na szukaniu odpowiednich parametrów, korzystając z odpowiednich algorytmów do szybkiego i efektywnego wybierania odpowiednich wartości. Niestety z powodu braku do przeszukiwania przestrzeni hiperparametrów wybrałem tylko stałą uczącą i rozmiar partii. Dodatkowo liczba epok i iteracji jest bardzo niska, odpowiednio 2 i 4 :(

In [9]:
```python
def objective(trial):
    learning_rate = trial.suggest_float("learning_rate", 1e-5, 1e-1, log=
    batch_size = trial.suggest_int("batch_size", 16, 128)

    transform = transforms.Compose([
        transforms.ToTensor(),
    ])

    trainset, valset = data.random_split(
        torchvision.datasets.CIFAR10(
            root="./data", train=True, download=True, transform=transform
        ),
        lengths=(.9, .1),
        generator=torch.Generator().manual_seed(2137)
    )
    trainloader = DataLoader(
        trainset, batch_size=batch_size, shuffle=True, num_workers=worker
    )
    valloader = DataLoader(
        valset, batch_size=batch_size, shuffle=False, num_workers=worker_
    )

    testset = torchvision.datasets.CIFAR10(
        root="./data", train=False, download=True, transform=transform
    )
    testloader = DataLoader(
        testset, batch_size=batch_size, shuffle=False, num_workers=worker
    )

    classes = ("plane", "car", "bird", "cat",
            "deer", "dog", "frog", "horse", "ship", "truck")

    # Create the ForceNet (LeNet-5 and ResNet combination).
    model = ForceNet(layers=(2, 2), class_count=len(classes))

    # Move model to GPU if available
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    model = model.to(device)

    # Define the loss function and optimizer.
```

```python
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=learning_rate)

    train_and_validate(
        model,
        trainloader,
        valloader,
        criterion,
        optimizer,
        device,
        epoch_count=2
    )

    accuracy: float = test(model, testloader, criterion, device)

    return accuracy
```

Najlepsze uzyskane parametry

- Dokładność: 52.56%.
- Stała ucząca: 0.00999.
- Rozmiar partii: 67.

Powyższe wyniki wykorzystałem nieświadomie w pierwszej fazie treningu, więc wyszło bardzo przyzwoicie. Przeszukiwanie przestrzeni hiperparametrów to bardzo dobra metoda do zoptymalizowania jak najbardziej swojej architektury - wyciskania soku ;)